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Assessing property value impacts near utility-scale solar in the Midwestern United States

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ABSTRACT

Utility-scale solar energy project proposals have been accelerating exponentially in the United States (U.S.) as the energy transition from fossil fuels to renewables continues to unfold. While the emissions and economic related benefits of deploying large-scale solar photovoltaics (PV) for electricity generation are well documented, relatively less is known about their impact on nearby property values. This paper investigates the location of utility-scale solar facilities in the U.S. Midwest, the average home value in each relevant zip code, and whether the presence of a utility-scale solar project affects nearby property values in any manner. Our study includes 70 utility-scale solar facilities built in the Midwest from 2009 to 2022 using data from the Lawrence Berkeley National Laboratory. Alongside housing value data from Zillow (i.e., Zestimate), we incorporate additional data, including solar project size in installed capacity, rurality, and state. Using the difference-in-differences method, our results indicate that utility-scale solar projects increase nearby property values by roughly 0.5–2.0 %. Moreover, our results show that smaller projects have more of a positive impact on nearby property values than projects that are 20 megawatts or larger. Ultimately, having a better understanding of how these larger-scale solar projects impact property values is essential for a variety of stakeholders – especially local officials and property owners – as they are increasingly faced with making decisions about whether to permit the construction of these facilities in their communities.

1. Introduction

Addressing escalating climate change concerns while promoting sustainable development is one of the foremost challenges of our time. While climate change is caused by several factors, such as inefficient energy infrastructure and increasing energy demand [57], specifically using fossil fuels to generate electricity is a key element that spurs greenhouse gas (GHG) emissions. According to the United Nations [52] and the United States [54] Energy Information Administration (EIA) (2021), burning fossil fuels currently accounts for 75 % (globally) and 73 % (in the U.S.) of GHG emissions, respectively. In response, governments around the world, including the current Biden Administration in the U.S., views the transition from fossil fuels to renewable energy as a top priority. In the U.S., the Bipartisan Infrastructure Law paves the way for renewable energy development by upgrading existing energy storage systems [34], which will be able to accommodate new renewable energy infrastructure such as wind and solar. Further, the Build Back Better plan incentivizes additional solar installations by increasing the investment tax credit (ITC) back to 30 % for qualifying technologies for the next 10 years [47]. While renewable energy only currently accounts for about 20 % of total U.S. electricity generation [59], the growth of large-scale renewable energy projects in recent years can increase this percentage significantly. For solar energy in particular, the installed capacity is expected to triple by 2034, amounting to nearly 700 additional gigawatts (GW), or enough to power >100 million homes [7].

Compared to biomass, hydropower, and wind, which are the three most abundant renewable energy generation sources in the U.S., solar energy accounts for only about 1.8 % of total electricity generation, yet it is also one of the fastest growing energy sources in the country [55], and also globally [46]. In the U.S., around 72 % of the total solar energy capacity is in the form of utility-scale solar photovoltaics (PV), ground mounted solar generation greater than 5 megawatts (MW), and utility-scale PV has been growing at a rate of 42 % annually since 2010 [10]. In fact, the U.S. installed 20.2 GW of solar PV capacity in 2022, which increases the cumulative total to well over 1000 GW of total installed capacity [48].

While the benefits and costs of traditional forms of distributed solar PV, such as rooftop systems, are well documented (e.g., [43,56]),

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relatively less is known about the impacts of large, utility-scale projects, which are often built in rural or suburban communities. Compared to rooftop solar, utility-scale projects are usually located in strategic areas near substations and major transmission lines with more direct sun exposure. The first large-scale solar project can trace back to the 1990s, but the development of utility-scale solar has been growing at a historic rate only during the past decade or so [50]. The installed cost per watt of solar has also dropped about 85 % during the past decade due to technological innovations [58], which has further accelerated the energy transition. Utility-scale solar is being built all over the U.S., but a few regions are developing projects at a much faster pace than others. The South Atlantic region (e.g., the Carolinas, Georgia, etc.) has installed more utility-scale solar than any other region in the U.S., and California has the second highest utility-scale solar capacity by region [33]. Compared to these two regions, the Midwest, which has around 127 million acres of flat agricultural land, only started to see utility-scale solar development in the past 5–10 years [14]. While the Midwest offers less solar radiation compared to other regions like the Southwest, the agricultural land it has is great for solar development as most of the areas are flat with very few environmental constraints. Developers do not need as many environmental approvals for developing solar projects on agricultural land compared to developing on other areas, such as brownfields [2]. Moreover, several metropolitan areas in the Midwest, such as Chicago, Cincinnati, Columbus, and Minneapolis, have ambitious renewable energy goals for the near future [25], and Fortune 500 companies are also helping contribute to the demand. While most projects are still in the approval phase or currently under construction, it is expected that, just in the Midwest region, about 6.6 GW of utility-scale solar energy will be added to the grid by the end of 2024 [17].

While prior reports and papers have indicated that utility-scale solar can bring jobs and long-term economic benefits to rural communities [18,29,31,37], other studies have shown that these projects could possibly negatively impact local wildlife, food security, and nearby property values [51]. Among other concerns, the potential negative impacts to nearby home and land values are often brought up as a key factor for those parties opposing large solar energy projects. While there is a small, but growing, body of literature specifically investigating this topic, the results to date have been largely inconclusive. To briefly illustrate, property value impact studies done in both the United Kingdom (UK) and Massachusetts, where the solar projects under investigation were in more urban or suburban settings, suggested that there is a 1.7 % property value decline [19,30]. However, a different study looking at 956 unique solar projects across the U.S. concluded that there is no conclusive relationship between nearby solar projects and property values [1]. In addition, no prior studies have investigated these potential impacts across the entire Midwestern region of the U.S., an area that has millions of acres of flat agricultural land which can potentially be converted to utility-scale solar facilities, or partially converted via agrivoltaics.

Against this unique background, our paper first reviews the existing literature on the property value impacts of utility-scale solar. After a detailed discussion of our data and methods, we display the results of our various average property value models in the Midwestern states (see Fig. 1), and conclude with a final discussion that offers the novelty and significance of this study, including implications for future utility-scale solar development.

1.1. Prior literature

In general, property values are determined by several factors, including the size of a property, its orientation, number of bedrooms/bathrooms, air conditioning, distance to nearby cities, and many others. Among these, the features that increase property values are considered amenities, whereas disamenities do the opposite [13]. Amenities and disamenities not only include features within each property, but also features surrounding each property. There are hundreds of existing property value impact studies investigating if one specific feature outside of a property is amenity or disamenity; for example, according to several studies, open green space and rivers are amenities to nearby properties [13,23]. In most cases, proximity to nature is considered an amenity, while facilities that produce pollution are considered a disamenity. To illustrate, chemical plants, coal-fired power plants, and landfills all are examples of disamenities to property values [3,39,44].

While it is unclear whether utility-scale solar projects are considered

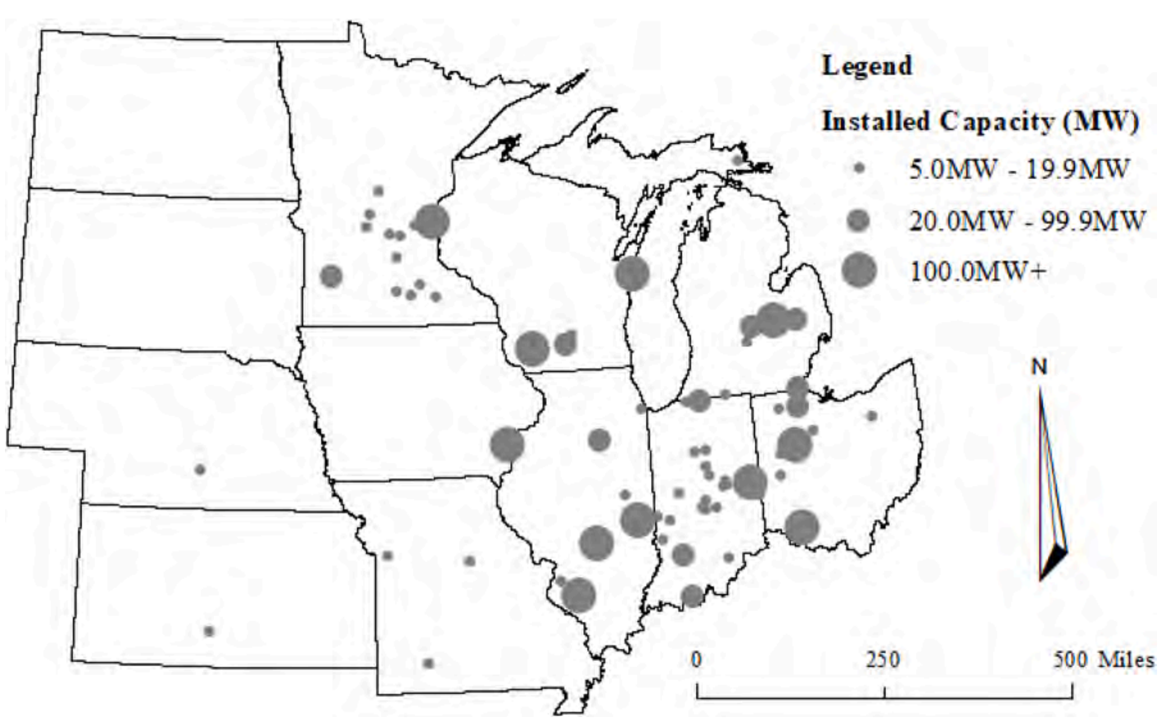

Fig. 1. Operational utility-scale solar facilities across the Midwest.

as an amenity or disamenity, public perceptions of these large solar projects can play an important role in determining property values. One study showed that about 70 % of Americans believed that utility-scale renewables were critical for the future of our energy supply, but the overall number of people who think that the energy transition and climate change should be a priority has been declining since 2019 [42]. The decline in overall awareness is largely due to the problem being relatively distant or remote from people's everyday lives, and, in recent years, appraisers have tended to associate utility-scale renewable installations with negative impacts to nearby properties [45]. Public perceptions, especially risk perceptions, can significantly affect housing values, and the effect can change when more assessments are completed [12].

1.1.1. Property value studies for utility-scale solar

While there is a small, but growing, body of literature investigating the property value impacts of utility-scale solar projects, the results have been largely inconclusive. Outside of the U.S., property value impact studies near large-scale solar projects done in South Korea and United Kingdom concluded that such solar projects could cause nearby property value declines of 5.0 % and 5.4 %, respectively [26,30]. In the U.S., studies done in the states of Massachusetts and Rhode Island used difference-in-differences (DID) methods and a hedonic pricing model that included environmental, neighborhood, and structural factors, and found that there is a 1.7 % housing value decline when there is a solar installation nearby [19,30]. To mitigate such impacts, a different study done in Portugal found that residents hoped to receive between $12.93–$56.64 per month for living close to utility-scale solar projects. This study investigated only three solar projects and created a questionnaire assuming that residents viewed utility-scale solar projects as disamenity [5]. Another study looking at 956 solar projects in the U.S. concluded that there is no real association between property values and nearby solar projects [1]. One of the most recent studies done by the Lawrence Berkeley National Laboratory showed that property values declined about 1 % depending on proximity to nearby solar projects, after investigating over 1.5 million housing transactions among 2000 solar projects in California, Connecticut, Massachusetts, Minnesota, North Carolina, and New Jersey [16]. Though there are no current studies, to the best of our knowledge, that show that having utility-scale solar nearby is a strong amenity per se, one study showed that 80 % of the residents in the U.S. support utility-scale solar projects in the country and specifically within their counties [10]. While some studies found negative associations between utility-scale solar and nearby property values, and some found no statistical significance, none of the prior studies have investigated the Midwest including all of the 12 states, an area that has millions of acres of flat agricultural land which potentially can be converted to utility-scale solar facilities.

In addition to the literature mentioned below and in Table 1, most large-scale solar projects have some kind of property value impact study done by the development companies or consultants prior to construction approval. There are two issues with these kinds of individual project studies. The first issue is that these studies are done only for their targeted areas, which are too specific and small to imply any regional trend. The second issue is that there can be a selection bias, as utility-scale solar development companies have a rational interest to avoid showing that their projects have a negative impact on these communities. Thus, only papers from academic institutions and studies that cover multiple projects from development companies were included in this section. In Table 1, in reverse chronological order, we show the key findings from five reputable studies that examine more than one solar project, all of which were done by academics or similar organizations.

1.1.2. Property value studies for other renewable energy sources

Though minimal research has been done regarding the property value impacts of utility-scale solar projects, similar questions have been well investigated for other renewable energy sources, such as residential solar PV and utility-scale wind. For residential solar, several studies have shown that buyers across various states, housing markets, and home types would consistently pay more for properties that have rooftop solar PV. In fact, in one paper, which examines 54 prior studies on renewable energy's impact on property values, rooftop solar is the only renewable source that creates consistent positive results [6].

On-shore wind energy is the most common renewable energy source in the U.S. [54], and it has a much longer history of development compared to utility-scale solar. Similar to utility-scale solar projects, most on-shore wind projects also tend to be in rural areas and occupy hundreds of acres of land [8]. A sufficient number of studies have been conducted regarding the property value impacts of being near wind projects, and a large majority of the results have showed no significance between property value and these wind projects (e.g., [21,60,61]). However, the property value impact of having wind turbines nearby can be different than utility-scale solar due to the difference in project acreage, as well as zoning regulations of wind energy development.

Though some existing research has indicated that large-scale solar projects might be a factor that causes nearby property value declines, some key research areas are still yet to be explored. To illustrate, most of the existing studies considered solar projects that are 1 MW or larger of installed capacity as "large-scale solar projects," but many projects larger than 1 MW can be set up as community solar projects instead of traditional utility-scale solar projects [36]. Distributed projects, including residential solar, community solar, and microgrid storage, are very different from utility-scale solar projects, and the property value

Table 1
Similar studies on the property value impacts of utility-scale solar.

Report/Paper Name (Year)	Author(s)	Publication/ Venue	Geography Investigated	Number of Projects Examined	Key Findings
Shedding Light on Large-Scale Solar Impacts: An Analysis of Property Values and Proximity to Photovoltaics Across Six U.S. States (2023)	Elmallah et al. [16]	*Energy Policy*	California, Connecticut, Massachusetts, Minnesota, North Carolina, and New Jersey	2000	Negative property value impact between −1.54 % to −0.82 %; depends on proximity to solar projects
Property Value Impact Study (2021)	Lines & McGarr[28]	Cohn Reznick, LLP	Michigan, Minnesota, Illinois, Indiana	6	No consistent negative impacts to nearby properties
Property Value Impact of Commercial-Scale Solar Energy in Massachusetts and Rhode Island (2020)	Gaur & Lang [19]	University of Rhode Island	Massachusetts and Rhode Island	284	1.7 % property value decline; property owners willing to pay $278 per year to avoid solar installation nearby
Solar Installations and Property Values (2019)	Marin[32]	University of Minnesota	Minnesota	32	Insignificant results on the relationship between solar installations and parcel values
An Exploration of Property-Value Impact Near Utility-Scale Solar Installations (2018)	Al-Hamoodah et al.[1]	University of Texas at Austin	Surveyed all 50 states in the U.S.	956	Mixed survey response, results showed that proximity to solar installation has no significant impact on home values

impacts of these kinds of solar projects can be specifically different due to ownership structure and related factors. Our study addresses the question of property value impacts of utility-scale solar projects by specifically only including projects that are 5 MW in installed capacity or larger (instead of 1 MW). Moreover, we explore the impact of *all* utility-scale solar projects in the Midwest, and no property value impact study of utility-scale solar projects has included all 12 states in this region before. Taken as a whole, our study fills an important research gap by more comprehensively investigating the relationship between property value and utility-scale solar projects in the Midwest, a region that experienced exponential growth in utility-scale solar project proposals and installations in the past handful of years.

2. Material and methods

Utility-scale solar project data and housing value data are two critical datasets that were utilized in this study. The utility-scale solar project data was gathered from the Utility-Scale Solar 2022 Edition Data File from the Lawrence Berkeley National Laboratory [4], a center that is part of the U.S. Department of Energy. The data file includes 1147 individual completed utility-scale solar projects that all are 5 MW in installed capacity or larger, and the projects come from 44 different states. For each individual project, the data file includes key information including installed capacity (in MW), longitude and latitude of the project (and, thus, zip code), the state which the project is located in, and the commercial operation date of the project. According to the U.S. Census Bureau [53], the Midwestern states include (in alphabetical order): Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin; for this study, only projects from those Midwestern states were selected. With 10 Midwestern states selected (other than North Dakota and South Dakota, which did not have any utility-scale solar projects in the data file), there were 83 utility-scale solar projects built from January 2009 to January 2022. The 83 individual projects included those that were under the same name but have different construction dates, and projects that had a different name but were located in the same longitude and latitude. It was important to exclude those projects because they were not unique to one specific area at a certain time period. After excluding those repetitive projects, 70 total projects were identified, and, thus, included in this study. The location of each project is shown as a gray circle in Fig. 1, and the difference in the size of the circle represents the amount of installed capacity. Based on the map, the number of projects by state was unevenly distributed, and there were more projects that are smaller than 20 MW in installed capacity than ones which were larger. Moreover, the timeline of newly operational projects was also unevenly distributed. As Fig. 2 shows, over 20 projects started operation in 2021, and about two-thirds of the 70 projects were built in the last five years.

Average housing value (AHV) data was gathered from Zestimate, a home value estimator database by Zillow. While collecting real transaction data would generate more accurate results, there were thousands of transactions happening each year near each utility-scale solar project site, which would make it extremely time consuming and costly to collect. Therefore, Zestimate was the best available dataset, and included information on home characteristics, listing price, prior sales, and market trends. The Zestimate dataset included AHV in almost any given month from January 2000 to June 2022 in every zip code. Zestimate differentiated property types, and because 3-bedroom houses were the most popular property types [20], this study only included the AHV of 3-bedroom houses. Additionally, since the number of bedrooms could affect housing value [22], only investigating 3-bedroom houses kept the dataset more specific and uniform. Finally, to merge the project location data and housing value data, the project location data, which was in longitude and latitude, was changed to the form of zip code.

As our study tracked AHV changes for each project over a long period of time, it was critical to account for inflation and extreme economic events such as COVID-19 and the 2008 housing crisis. For instance, it would be unfair to compare the AHV in March 2015 at zip code 55,056 to the AHV in April 2019 at the same zip code without including the effect of inflation and housing market fluctuation. Thus, the Case Schiller (CS) Index was included in this study to normalize the AHV. The CS Index is measured using data on repeated sales of single family homes over time, and this index had housing value by month from January 2000 [11] The CS Index has been used in several prior studies to better understand property values and housing market trends (e.g., [9,15,41]).

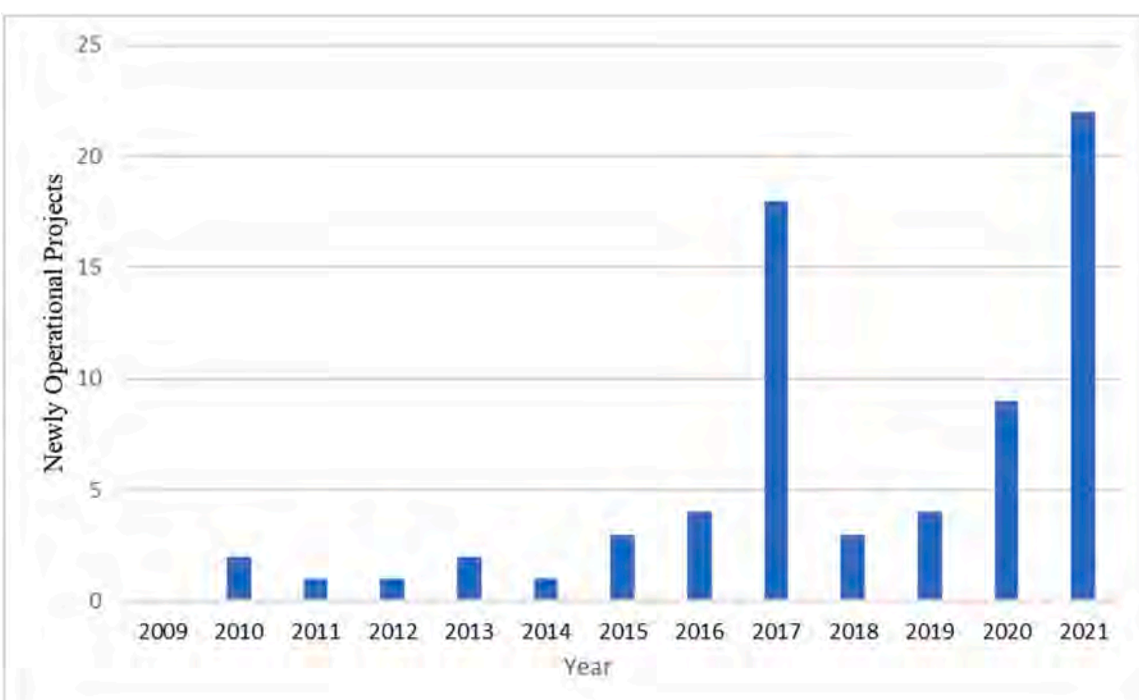

Fig. 2. Installation timeline of utility-scale solar projects in the Midwest.

As demonstrated in Fig. 3, in general, while AHV increased over time, it decreased from 2009 to 2012 following the 2008 economic crisis. While the CS adjusted value seemed to have a downward trend, it remained mostly constant from 2013 to 2019, which excluded the 2008 economic crisis and COVID-19. Thus, part of the study included CS adjusted AHV from 2013 to 2019, which is explained in later sections of this paper.

Rurality may be another significant factor that could affect housing value, and, according to the U.S. Department of Agriculture (USDA), each zip code in the U.S. has a rating between 1 and 10, with 1 being metropolitan and 10 being rural areas [24]. The rating classifications were primarily based on the size and distance of commuting flows, and to simplify the ratings and for ease of analysis, this study categorized ratings between 1 and 5 as metro, and 6–10 as non-metro, or "rural." To transfer this rating into binary variables, all metro areas were listed as "0," and all non-metro areas were listed as "1." The rurality ratings of each project are listed in Appendix A.

With project data, housing data, CS data, and rurality data all being collected, our next step was to arrange them into one spreadsheet. For each utility-scale solar project, monthly AHV was tracked from March 2009 to June 2022, so given 160 months, 70 unique utility-scale solar projects, and the treatment and control groups (see Section 3.1), 22,400 unique data entries were collected. However, because Zestimate missed some AHV data for some zip codes, only 20,815 data entries had actual AHV values. For the CS-adjusted data, since only the AHV between January 2013 to December 2019 were included (excluding the COVID-19 years and 2008 housing market recovery years), only 35 projects out of 70 projects were counted, which left 5778 usable zip code-year combinations with actual AHV values.

2.1. Treatment and control group definitions

To examine the relationship between utility-scale solar projects and nearby property values, we set up each solar project to have a treatment group and a control group. The treatment group for each project included the zip code which has a utility-scale solar project, and the control group for that project included a randomly selected zip code which geographically touched the treatment zip code. The control zip code did not have a utility-scale solar project and was in the same state as the treatment zip code. In binary variable terms, the treatment zip code was marked as "1," and the control zip code was marked as "0."

With the treatment group and control group established, the next group of variables were pre- and post-operation. Based on the hypothesis, it was expected that the change in AHV in the treatment group after the project started operating would be different than the change in AHV before the project operational date. For example, if the operational date of a project was March 2012, all months from March 2009 to February 2012 would be considered as pre-operation, and, in binary variable terms, it was marked as "0." Any month from March 2012 to June 2022 for that project would be considered as post-operation, and, in binary variable terms, it was marked as "1." The binary variable was labeled as "Post." For the control group, Post would be 1 when the project in the treatment group started operation. Though "Post" would be a required variable in a standard DID method, "Post" was not included as an individual variable because it was absorbed by the "Year" fixed effect as they are similar chronological variables.

Under the hypothesis that there was an association between housing value and nearby utility-scale solar projects, the AHV in the treatment group after operation would be statistically significantly different compared to other groups, including the control group after operation or treatment group before operation. Therefore, the statistical significance of AHV differences in the treatment group after operation indicated if utility-scale solar projects had some impact on nearby property value. Since the new variable, treatment group after operation, was based on the treatment group and post-operation variables, the new variable is shown as "Treated*Post" in the formula. The variable "Treated*Post" is also a binary variable, treatment group after operation is 1, and 0 otherwise.

"Treated" and "Treated*Post" were the required variables to determine the association between housing value and nearby utility-scale solar projects. However, other factors such as rurality, state, project size, and operational date might also affect property values, and adding those variables would increase the accuracy of the results. State was included as a categorical variable, and each data entry had one state which the project located in Next, project size in installed capacity was organized into a binary form, in which 1 indicates projects that were smaller than 20 MW, and 0 otherwise. There are many definitions of

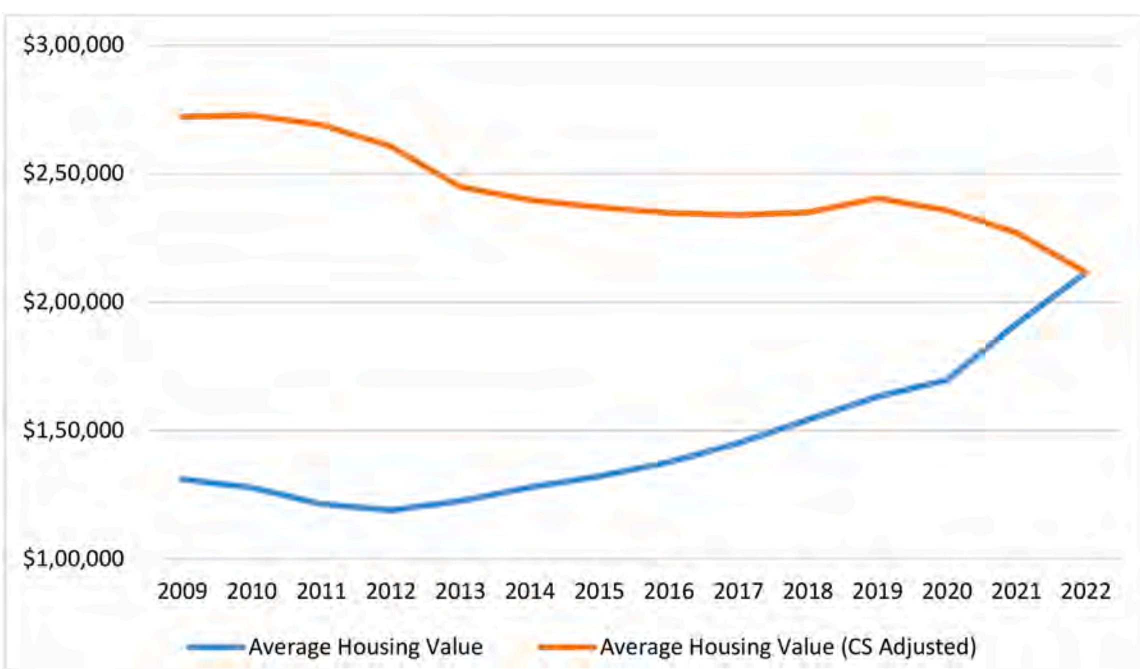

Fig. 3. Housing value trend timeline (normal and case schiller adjusted).

what the minimum size of a utility-scale solar project is, and the most popular figures are 5 MW and 20 MW [38]. So then, our size variable not only showed results from two definitions, but also determined if project size was a statistically significant factor for nearby property values. We also included year as a categorical variable, which could account for economic recessions, housing market fluctuations, and inflation, and this variable was only applicable for non-CS adjusted values as CS accounted for some of those factors. Finally, county and zip code were included as categorical variables, which could determine the differences of AHV between different areas (Table 2).

2.2. Equations and difference-in-differences method

After obtaining the data and developing these variables, our next step was to use a statistical method to analyze the data entries and determine the association. As shown in Appendix B, because the data was not perfectly randomized on an individual level, and there were many repeated cross-sectional data, it was best to use the DID method. While the property value study done in Rhode Island and Massachusetts [19] also utilized a DID analysis, the dataset and variables were rather different. Due to the amount of data entries, and the variety of variables that were available in this study, three different models were created to test the hypothesis. All three models included Treated, Treated*Post, Rurality, Size, Year, Constant (C), yet State, County, and Zip Code were not used in all models. All three models were run twice, once with normal unadjusted AHV, and once with CS-adjusted AHV. All three models were tested via Stata using confidence intervals of 90 %, 95 %, and 99 %, which is standard for studies of this variety.

All three models had the exact same variables other than the fixed effects. For the first model, the fixed effect was "State," for the second model it was "County," and for the third model it was "Zip Code." The change in fixed effects can help determine the consistency of the overall results. By adding the richness of the variables from State to Zip Code, the results in Model 3 would have the highest adjusted R^2 value, which would give the results more validity. With the unadjusted AHV, each model contained 20,815 data entries and accounted for all 70 utility-scale solar projects in our sample. For the CS-adjusted AHV, each model included 35 out of 70 total projects, which represented 5778 unique data entries. Because each model was run twice, there were six results. The equation of property (location x) sale price (P) at time (t) is:

Model 1: State Model

$$P_{xt} = \beta_1 * Treated_{xt} + \beta_2 * (Treated_{xt} * Post_{xt}) + \beta_3 * Rurality_{xt} + \beta_4 * Size_{xt} + \beta_5 * Year_{xt} + \delta_{st} + C + E$$

Model 2: County Model

$$P_{xt} = \beta_1 * Treated_{xt} + \beta_2 * (Treated_{xt} * Post_{xt}) + \beta_3 * Rurality_{xt} + \beta_4 * Size_{xt} + \beta_5 * Year_{xt} + \delta_{ct} + C + E$$

Model 3: Zip Code Model

$$P_{xt} = \beta_1 * Treated_{xt} + \beta_2 * (Treated_{xt} * Post_{xt}) + \beta_3 * Rurality_{xt} + \beta_4 * Size_{xt} + \beta_5 * Year_{xt} + \delta_{xt} + C + E$$

Again, the fixed effects are different between the three models. There are 12 states in the state variable, 60 unique counties in the county variable, and 70 unique zip codes in the zip code variable. The increase in the richness of the fixed effects increased the accuracy of the results, and the consistency of the results were shown when comparing all three models.

Table 2
Definitions of variables included in this study.

Variable	Definition
P_{xt}	Housing pricing at zip code x at time t
$Treated_{xt}$	Binary variable, 1 for the treatment group, 0 for the control group
$Post_{xt}$	Binary variable, 1 for after operation, 0 for before operation
$Rurality_{xt}$	Binary variable, 1 for non-metro zip codes, 0 for metro zip codes
$Size_{xt}$	Binary variable, 1 for projects with an installed capacity between 5 and 20 MW, 0 for projects with an installed capacity larger than 20 MW
$Year_{xt}$	Categorical variable, each year is in its own category
δ_{st}	State fixed effect
δ_{ct}	County fixed effect
δ_{xt}	Zip code fixed effect
C	Constant
E	Standard Error

3. Results

3.1. AHV comparison with different variables

Comparing the AHV of each group was the simplest and the most direct way to visualize the differences. Table 3 uses the unadjusted AHV of the 70 projects in the Midwest from January 2009 to June 2022, and it included most of the variants used for all three models under the "Variant" column. "Mean Housing Price" presented the statistical average of the AHV of each variant, and all of the mean housing prices were compared to the overall mean housing price. The table also includes the minimum, maximum, and standard deviation of each mean housing price.

As Table 3 indicates, the overall mean was $145,317, and the treatment group and control group were relatively close to this overall mean. Other than the treatment group and the control group, all other variants had relatively significant differences when compared to the overall mean. AHV near projects that were between 5 and 20 MW in installed capacity were higher than the ones that were not. For projects that were located in metro areas, the AHV was $4694 greater than the overall mean, which indicated that the AHV in metro areas was higher than the AHV in rural areas.

The AHV of post-operation was also compared to the overall mean. Since housing prices traditionally increase over time, it was expected that housing price after operation, such as in 2020, would be higher than before operation, such as in 2013. Table 3 shows that "Overall Post," which included all housing prices after operation, was $23,216 higher than the overall mean. Similarly, "Control Post" and "Treated Post" both had higher AHV than the overall mean.

Since this study also involved models which included CS-adjusted housing values, Fig. 4, an AHV comparison graph, demonstrates the

Table 3
Summary statistics.

Variant	Mean Housing Price	Minimum	Maximum	Standard Deviation	Comparison to Overall Mean
Treatment Group	$145,327	$32,137	$504,682	$56,648	10$
Control Group	$145,307	$51,743	$426,922	$55,268	−10$
5 MW–20 MW Projects	$150,011	$32,137	$504,682	$57,701	$4694
>20 MW Projects	$134,059	$63,290	$408,221	$49,735	-$11,258
Metro Projects	$150,001	$32,137	$504,682	$58,650	$4684
Non-Metro Projects	$127,236	$63,290	$320,201	$39,043	-$18,081
Control Post	$170,511	$58,540	$426,922	$63,237	$25,194
Treated Post	$166,558	$35,051	$504,682	$63,051	$21,241
Overall Post	$168,533	$35,051	$504,682	$63,171	$23,216
Overall Mean	$145,317	$32,137	$504,682	$55,949	$0

Fig. 4. AHV comparison graph.

difference between CS-adjusted housing value and normal housing value. For the unadjusted AHV, both treated and control groups saw an increase in AHV, which was expected because AHV increases over time. For the CS-adjusted AHV, both control and treated groups have similar AHV values throughout. Overall, the CS-adjusted AHV had much higher values than the unadjusted numbers because the CS-adjusted AHV were adjusted to December 2019 AHV. Based on the graph, there was not a clear association between utility-scale solar projects and nearby property value. Thus, our DID models offer more detailed results.

3.2. Difference-in-differences results

Below, Tables 4 and 5 include the three DID models, and the statistical significance is marked with an asterisk (*) sign after the coefficient. The different number of asterisks represent different statistical significance levels. For the "State," "County," and "Zip Code" fixed effects, the coefficients were significant at 99 % confidence level, and because the fixed effects were different in the three models, the coefficients of those fixed effects were not listed in Tables 4 and 5.

Each model in Table 5 included 20,815 total observations including all 70 projects from March 2009 to June 2022, and in Table 4, there were 5778 observations for each model because only 35 projects from January 2013 to December 2019 were included. The R^2 indicates how much variance is explained in the model. Model 3 for both normal AHV and CS-adjusted AHV explained over 94 % of the overall AHV outcome, and Model 3 is generally considered the most robust and reliable model. The high adjusted R^2 was due to the large number of unique zip codes in Model 3. Model 2, the County model, explained over 80 % of the overall AHV outcome, and Model 1, the State model, explained over 55 % of the overall AHV outcome.

Despite all three models not having the same fixed effects, the first five variables existed in all three models. β_1 represented the AHV difference between treatment group and control group before any solar project was introduced. A negative coefficient indicated that the treatment zip code had an overall lower AHV compared to the control zip code before any utility-scale solar installation. Since the "Treated" variable was measured on a zip code level, Model 3 counted the zip code variable twice, as it had a zip code variable as a fixed effect. Since DID cannot identify the zip code-specific effect in a model with zip code fixed effect, β_1 in Model 3 was unidentified. Among Model 1 and Model 2, three out of the four β_1 showed statistical significance. The results from Model 1 and Model 2 indicated that before utility-scale solar projects

Table 4
DID property value impact CS adjusted AHV analysis.

Variables/Models	Model 1: State	Model 2: County	Model 3: Zip Code
Treated VS Controlled (β_1)	−1458	−3338***	Unidentified
Property Value Impact (β_2)	−662	2640**	700***
Rurality (β_3)	−25,563***	−22,166***	Unidentified
Project Between 5–20 MW Installed Capacity (β_4)	13,620***	50,206***	23,200***
Constant (C)	177,335***	158,793***	143,235***
Numbers of Observations (n)	5778	5778	5778
Standard Error (E)	12,472	2670	2443
R^2	0.5642	0.8209	0.9897
Adjusted R^2	0.5629	0.8197	0.9895

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 5
DID property value impact CS normal AHV analysis.

Variables/Models	Model 1: State	Model 2: County	Model 3: Zip Code
Treated VS Controlled (β_1)	−2921***	−2976***	Unidentified
Property Value Impact (β_2)	2004**	1310**	3199***
Rurality (β_3)	−21,910***	−10,425***	Unidentified
Project Between 5–20 MW Installed Capacity (β_4)	19,492***	779	8357***
Constant (C)	94,369***	185,827***	143,235***
Numbers of Observation (n)	20,815	20,815	20,815
Standard Error (E)	9985	21,281	18,388
R^2	0.5880	0.8158	0.9483
Adjusted R^2	0.5875	0.8151	0.9479

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

were developed, the treatment areas had relatively lower AHV compared to the controlled areas. This difference in AHV can be as large as $3338, depending on the models.

The coefficient β_2 demonstrated the impact of utility-scale solar projects on nearby property values by comparing the treatment group after operation to other variable combinations. Other than the normal AHV Model 1, all other models in both normal AHV and CS-adjusted AHV showed positive statistical associations. Based on Tables 4 and 5, there was a positive association between utility-scale solar projects and nearby property value, from $700 to $3199, depending on the model. This coefficient equates to a 0.5–2.0 % property value *increase* with utility-scale solar nearby, and the consistency between results in all models further strengthens this outcome.

Rurality was yet another factor that could potentially affect property values, and the coefficient of β_3 indicated this relationship. A negative coefficient showed that properties in non-metro areas had lower AHV than properties in metro areas. The coefficients of rurality in Model 3 were unidentified because the rurality variable, which was measured at the zip code level, was not independent to the zip code fixed effect. Results from Model 1 and Model 2 indicated that properties in rural areas had significantly lower AHV than properties in metro areas. Based on the coefficient, rurality was the most impactful variable other than the "Year" variable. β_4 differentiated the AHV between properties that were near smaller projects (5–20 MW of installed capacity) and properties that were near larger utility-scale solar projects (greater than 20 MW of installed capacity). Five out of the six results here showed statistical significance. Thus, our results indicate that properties near smaller projects had a higher AHV than properties near larger projects.

4. Discussion

Overall, our work aimed to better discern if large solar projects had any sort of impact on property values as part of broader discussion of how and where to build such projects. Among other factors, distance to interconnection points to the grid, solar radiation, and local zoning ordinances are some of the reasons that solar developers choose certain geographies to build a project. As our models suggested, there was a negative statistical association between the treatment group and the control group, and these results indicate that the sites that developers selected had lower property values (i.e., costs) than the areas they did not select. However, the magnitude of the effect was relatively minimal, as the treatment group only had between 2.0–3.1 % lower AHV than the control group. While stakeholders such as local officials and landowners would simply think that developers would choose a site due to the low cost of the land, there are several additional factors that can influence the site selection process [37,49]. Assuming solar resources being equal, lower AHV in most cases is equal to lower land value, and it would be logical that developers would choose areas that had slightly cheaper land to develop projects compared to the surrounding areas.

Though the magnitude of effect of utility-scale solar and property value impacts were somewhat small, the associations were still statistically significant. Five out of our six models showed positive associations at the 95 % confidence level or higher, with the coefficient between $700 to $3199. The only model that did not show any statistical significance was the State model, which had the lowest adjusted R^2 value among all six. These coefficient values translate to a 0.5–2.0 % increase in AHV when there is a utility-scale solar project nearby. Both normal AHV and CS-adjusted AHV indicated similar results, further strengthening our finding of this directional relationship between property values and utility-scale solar projects. The positive correlation between utility-scale solar projects and nearby property values could be due to the new tax revenues, which are often used to support local schools and other public services, as well as the local employment opportunities that utility-scale solar projects can provide. Many utility-scale solar developers also engage with local communities by hosting landowner meetings and supporting other events such as county fairs, and those benefits to the local communities could perhaps increase the AHV as well. It is also worth noting that our results were different from many prior studies, as several indicated that there would be slight negative association between utility-scale solar projects and nearby property values.

It was expected that rural property values would be less than metro property values, which was shown in both Models 1 and 2. Rurality is one of the most impactful factors for property value impacts, and our coefficient were between -$10,425 to -$25,563. Moreover, AHV near projects that were between 5 and 20 MW of installed capacity were higher than the AHV of those near larger projects. Smaller projects, especially projects that were around 5 MW in installed capacity, could be easily hidden with vegetative buffers, and stakeholders are less likely to physically see these projects [10].

While the statistical findings of our study were different from several prior papers, most of the studies showed that the magnitude of impact which utility-scale solar projects had on nearby property values were relatively minimal. Both the Massachusetts and Rhode Island study and the Lawrence Berkeley National Laboratory study indicated that the negative impact was <2 %. Those two studies also indicated that other factors, such as number of bedrooms and location of the property, were much more impactful than the influence of utility-scale solar projects. Similarly, in this study, other factors such as rurality and state affected property values at a much higher magnitude than having a utility-scale solar project nearby. Put another way, many prior studies showed that utility-scale solar projects are not the main driving factor for the change or differences in property values, and our study showed the same.

A novel contribution of our study is that no prior study has investigated over 70 projects in one geographical region within the U.S. (i.e., the Midwest). Instead, most of the property value impact studies target specific projects and specific audiences, such as local or state government officials. However, as the results of zip code, county, states, and other variables showed in this study, the impact of each project can be drastically different from one another. Most of the prior property value studies, which only investigate one or two solar projects, cannot represent the broader impact of all utility-scale solar projects. This is further important as project proposals seemingly emerge weekly in this region.

Understanding the property value impacts of utility-scale solar projects in the Midwest not only helps stakeholders such as landowners and local officials better comprehend the overall costs and benefits of utility-scale solar projects, but it also generates ideas for potential policy change in the future, should they be achievable in complex regulatory environments [35]. For instance, many counties in the Midwest still require utility-scale solar projects to be at least 500 feet away from the nearest property (i.e., the setback rule), and this has been one of the toughest obstacles for the development process [27]. As our study showed, the effect of utility-scale solar projects on nearby property values was actually positive in both rural and metro areas, and, thus, local officials could perhaps relax the regulations on how far these projects need to be away from nearest residence. In addition, as most studies have found that the magnitude of impact which utility-scale solar projects had on nearby property values were relatively small, and in our case were positive, local and state officials could create pathways for projects to get approved easier (e.g., with less impact studies required) in order to meet Renewable Portfolio Standards and other renewable energy and decarbonization goals as part of a broader energy roadmapping effort [40].

There are some limitations to our study, both in the data collection process and methods, which are worth noting. For instance, using data from Zestimate and categorizing projects by zip code may be less accurate than using real transaction data and sight lines or radii for geographic bounds. Nevertheless, the benefit of using Zestimate in this study was to ensure that there would be a value for every zip code at every month. Further, using zip codes for housing locations is less accurate than coordinates, and not every solar project is located directly in the center of each zip code area, impacting the accuracy. Finally, using binary variables in several places, while easier to interpret, may not always be detailed enough, such as in how the property value impact of a 200 MW solar project may be very different than a project that is 20 MW. Similarly, many suburban areas under the binary framework were considered as “Metro,” and less than one-third-of all projects were considered as “non-Metro.”

Finally, a few ideas for future research emerged from this study. First, instead of using zip code as a unit, future studies could include a parameter for each project via GIS (such as miles or kilometers away), ensuring that a project is always at the center of the parameter, therefore increasing the accuracy of the results. Further, to determine the property value impacts of utility-scale solar projects across the entire U.S., studies could randomly select projects from each geographical region to generate results that are applicable to all projects. Moreover, while we have speculated that one of the reasons that we are seeing an increase in property values is from the new economic activity in these areas via tax revenues that are being fed into communities, future studies should attempt to move beyond correlations and attempt to pinpoint the exact driver(s) of “why” property values are changing.

CRediT authorship contribution statement

Simeng Hao: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gilbert Michaud:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Investigation, Conceptualization.

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Utility-Scale Solar Projects in the Midwest with Key Data

Project	Operation Date	State	Solar Capacity (MW-DC)	Zip Code	Non-Metro (Rurality)
Riverstart Solar Park	12/31/2021	IN	268.00	47,358	1
Hillcrest Solar	7/30/2021	OH	260.00	45,154	0
Prairie Wolf Solar	11/30/2021	IL	255.00	61,938	0
Two Creeks Solar	11/30/2020	WI	213.00	54,241	0
Hardin Solar Energy (Hardin I)	2/28/2021	OH	199.30	45,812	0
Badger Hollow I	11/30/2021	WI	191.60	53,569	1
Assembly Solar II	12/31/2021	MI	161.00	48,449	0
North Star Solar Project	10/20/2016	MN	138.00	55,056	0
Dressor Plains Solar	9/30/2021	IL	135.40	62,080	1
Prairie State Solar Project	7/30/2021	IL	132.30	62,237	1
Wapello Solar	3/31/2021	IA	127.50	52,653	1
Marshall Solar Project	1/9/2017	MN	93.16	56,258	0
Assembly Solar I	12/31/2020	MI	72.30	48,817	0
Troy Solar	4/30/2021	IN	64.70	47,588	1
Lapeer Solar Project I (Demille Array)	5/1/2017	MI	34.57	48,446	0
Temperance Solar	12/31/2020	MI	29.60	48,133	0
Bingham Solar	12/31/2020	MI	29.40	48,879	0
Bowling Green Solar	1/19/2017	OH	28.70	43,402	0
St. Joseph Solar	3/31/2021	IN	25.40	46,530	0
NSA Crane Solar Project	2/27/2017	IN	24.30	47,553	1
O'Brien Solar Fields	5/31/2021	WI	24.13	53,711	0
Grand Ridge Solar Plant	7/27/2012	IL	22.76	61,364	0
Delta Solar Power II (DSP-II $A + B$, Delta Solar Power Project)	7/30/2018	MI	19.40	48,837	0
Logansport Solar	9/30/2021	IN	19.30	46,947	0
Electric City Solar	12/31/2020	MI	18.90	49,091	0
Wapakoneta-Pratt	11/30/2021	OH	17.30	45,895	0
Aurora Waseca Solar	6/30/2017	MN	15.92	56,093	1
Aurora Paynesville Solar	6/30/2017	MN	15.24	56,362	1
Aurora Albany Solar	6/30/2017	MN	15.24	56,307	0
Truman Solar	6/30/2021	MO	14.00	65,201	0
Indy Solar I	12/16/2013	IN	13.90	46,259	0
AES Belleville Solar LLC	9/30/2021	IL	13.30	62,220	0
IMPA Crawfordsville 5 Solar Park	9/30/2020	IN	13.24	47,933	0
DG AMP Solar Piqua Manier	7/30/2019	OH	13.20	45,356	0
IND Airport Solar Farm Phase 2 (INDY II + III)	9/30/2015	IN	13.20	46,241	0
Camp Ripley Solar	1/31/2017	MN	13.10	56,345	1
IMPA Peru 2 Solar Park	4/30/2021	IN	12.60	46,970	0
Northern Cardinal Solar SCS IL 1, LLC (Solar Farm 2.0)	2/28/2021	IL	12.30	61,822	0
Aurora West Waconia Solar	6/30/2017	MN	12.25	55,397	0
PSEG Wyandot Solar Facility	3/15/2010	OH	12.02	43,351	1
Indy Solar III	12/16/2013	IN	11.90	46,221	0
IMPA Richmond 5 Solar Park	6/30/2021	IN	11.90	47,374	0
Dane County Airport Solar	12/31/2020	WI	11.40	53,704	0
IMPA Anderson 3 Solar Project	12/31/2021	IN	11.34	46,013	0
Indianapolis Motor Speedway (IMS) Solar Farm	7/31/2014	IN	11.20	46,222	0
Nixa Solar Farm	11/14/2017	MO	11.09	65,714	0
Aurora Lake Pulaski Solar	6/30/2017	MN	10.92	55,313	0

(*continued on next page*)

(*continued*)

Project	Operation Date	State	Solar Capacity (MW-DC)	Zip Code	Non-Metro (Rurality)
Independence II Solar Farm (IPL2, Bundschu)	6/30/2018	MO	10.87	64,056	0
IMPA Anderson 2 Solar Project	12/30/2017	IN	10.20	46,011	0
Exelon City Solar (West Pullman Industrial Redevelopment Area)	7/1/2010	IL	10.00	60,643	0
Aurora Dodge Center Solar	6/30/2017	MN	9.90	55,927	0
BNB Napoleon Solar Phase 1	12/23/2011	OH	9.79	43,545	1
IMPA Scottsburg Solar Park	10/31/2020	IN	9.75	47,170	0
Aurora Annandale Solar	6/30/2017	MN	9.12	55,302	0
Athens MN CONX (Ventyx: Connexus Energy (Athens))	12/31/2018	MN	8.84	55,040	0
DG AMP Wadsworth 1048	12/31/2019	OH	8.60	44,281	0
Aurora Eastwood Solar	6/30/2017	MN	8.23	56,001	0
Aurora West Faribault Solar	6/30/2017	MN	7.89	55,021	0
City of Pratt Solar (Pratt Solar Farm)	3/31/2019	KS	7.67	67,124	1
Pickford Solar	2/28/2021	MI	7.60	49,774	0
Connexus Solar Stanford 1STF (Sunflower)	5/31/2021	MN	7.30	55,070	0
Kearney NPPD Solar Project	12/11/2017	NE	7.25	68,847	0
Kokomo Solar Park (Kokomo Solar 1)	12/29/2016	IN	7.15	46,902	0
McDonald Solar Farm	12/26/2015	IN	7.14	47,885	0
Sullivan Solar	9/1/2016	IN	7.00	47,882	1
Pastime Farm	12/26/2015	IN	6.93	47,834	0
Olive Solar Power Project	9/1/2016	IN	6.47	46,552	0
Tipton Solar Park	7/30/2019	IN	6.30	46,072	1
Middleton Municipal Airport Solar (Morey Field)	7/30/2020	WI	6.30	53,562	0
IMPA Anderson 1 Solar Project	1/23/2017	IN	6.20	46,001	0

Appendix B. Utility-Scale Solar Overview by State, Project Size, and Rurality

State/Project Size & Rurality	100 MW+	20 MW–100 MW	5 MW–20 MW	*Total*	Non-Metro	Metro
Iowa	1	0	0	*1*	1	0
Illinois	3	1	3	*7*	2	5
Indiana	1	3	18	*22*	5	17
Kansas	0	0	1	*1*	1	0
Michigan	1	4	3	*8*	0	8
Minnesota	1	1	12	*14*	3	11
Missouri	0	0	3	*3*	0	3
Nebraska	0	0	1	*1*	0	1
Ohio	2	1	5	*8*	2	6
Wisconsin	2	1	2	*5*	1	4
Total	**11**	**11**	**48**	***70***	**15**	**55**

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